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ORIGINAL ARTICLE

The analysis of groundwater levels influenced by dual factors in western Jilin Province by using time series analysis method

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Abstract To enhance our understanding of the dynamic characteristics of groundwater level in the western Jilin Province of China, two models of decomposition method in time series analysis, additive model and multiplicative model, are employed in this study. The data used in the models are the monthly groundwater levels of three wells observed from 1986 to 2011. Moreover, the analysis of three wells, located in the upper, middle and downstream of the groundwater flow path, helps to obtain the variation in each well and the mutual comparison among them. The final results indicate that the groundwater levels show a decreasing trend and the period of variation last for about 7 years. In addition, hydrographs of the three wells manifest the impacts of human behavior on groundwater level increases since 1995. Furthermore, compared with the autoregressive integrated moving average model, the decomposition method is recommended in the analysis and prediction of groundwater levels.

Keywords Groundwater level · Time series analysis · ARIMA model · Forecasting · Western Jilin Province

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Introduction

Western Jilin Province is located at the northern corner of China and its ecological environment is sensitive and vulnerable (Huang and Meng 1996). The health of the ecological environment has a strong dependency on groundwater level (Zhang et al. 2003). Therefore, the study of the dynamic characteristics of groundwater levels is important to the ecological environment in western Jilin Province.

Groundwater level time series usually exhibit complex fluctuations due to interactions of many factors, and therefore we need mathematical methods to decompose the complex series and study their variations. Time series analysis has been widely used in groundwater resource evaluation, forecast, and management because of its simple, easy to use and practical features. Most of the research articles (e.g., Liang 2011; Yang et al. 2009; Erdogan and Gülal 2009; Zhao et al. 2007; Zhou et al. 2007; Hu et al. 2001) decompose the groundwater level time series into trend, periodicity, and random components to study their characteristics, then combine the three together as an additive model to forecast when using this method.

However, this method of decomposition may not apply to all types of hydrogeological conditions. Moreover, these research articles have investigated the data observed in a single well and lack the analysis of the whole region. Thus, the following hypotheses are addressed:

1. In theoretical aspect, this paper uses both additive and multiplicative models (Robert and Charles 1991; Zhang and Yang 2005) of the decomposition method to explore whether they fit different hydrogeological conditions. In addition, this paper uses not only trend, and periodic and random components to extract the time series, but also

the seasonal component (Wang 1997) to understand the variation characteristics in the year.

2. This paper studies three wells, located in the upper, middle and downstream of the groundwater reservoir in the area to investigate the interactions and differences among them.

This paper studies the dynamic characteristics of groundwater levels influenced by both natural and human factors in the western Jilin Province. Natural factors mainly include rainfall, evaporation and solar activity, while human factors mainly refer to human exploitation of the groundwater. This paper first establishes the additive and multiplicative models of groundwater level in three wells to study the dynamic characteristics of groundwater level by coding in Matlab. The second step involves analyzing and discussing the causes of the variations in trend, seasonal, periodic and random components. The third step forecasts the groundwater levels in the next 3 years by both additive and multiplicative models. The fourth step compares the consistency of groundwater levels among the upper, middle and downstream areas to compare the associations and differences among them. Finally, to validate the dependency of the decomposition method, an autoregressive integrated moving average model (ARIMA model) is compared for the prediction of groundwater levels.

Methods

Additive and multiplicative models are two common models in the decomposition method. After passing the test, it can be used for forecasting. The basic equation is:

$$\text{additive model}: \quad H(t) = X(t) + S(t) + P(t) + R(t) \tag{1}$$

$$\text{multiplicative model}: \quad H(t) = X(t) \times S(t) \times P(t) \times R(t) \tag{2}$$

where $H(t)$ is the time series, $X(t)$ the trend component, $S(t)$ the seasonal component, $P(t)$ the periodic component, and $R(t)$ is the random component.

Trend component stands for the general trend of one series. It is extracted by the smoothing method or polynomial fitting method in traditional ways; however, this study uses moving average twice and then adopts stepwise regression method (Lu et al. 2012) to extract the trend component. After calibrating the input parameters, the degree of fitting is increased to more than 0.8, while the traditional method of fitting is about 0.7. On completing the extracting trend component, the trend is removed. When using the additive model, it is removed by minus, that is to say $H(t) - X(t)$ is the series to be decomposed in the next step. When using the multiplicative model, the trend is removed by division, that is to say $H(t)/X(t)$ is the series to be analyzed in the next step.

The seasonal component exhibits the variation of series during the year. It is extracted by the multi-year average method. 12 values standing for the weights of 12 months is generated after averaging $H(t) - X(t)$ (additive model) or $H(t)/X(t)$ (multiplicative model) of the same month data in different years. After extracting the seasonal component, it is then removed. $H(t) - X(t) - S(t)$ is the series to be analyzed in the next step of the additive model and $H(t)/X(t)/S(t)$ the series to be investigated in the next step of the multiplicative model.

Periodic component stands for the interannual variability of the series. Harmonic wave analysis method is adopted to extract the periodic component. This method considers that the periodic component is composed of many different cycle waves and can be expressed by the Fourier series.

$$\hat{P}_t = \frac{a_0}{2} + \sum_{k=1}^{L}\left[a_k \cos\frac{2pkt}{n} + b_k \sin\frac{2pkt}{n}\right] \tag{3}$$

where $\hat{P}_t$ stands for the estimated value of p_t, L the amount of waves, K the number of waves, a_k, b_k are coefficients and n is the number of samples. Its formula is:

$$a_0 = \frac{1}{n}\sum_{t=1}^{n} x(t); \tag{4}$$

$$a_k = \frac{2}{n}\sum_{i=1}^{n} P_i \cos\frac{2pki}{n}; \tag{5}$$

$$b_k = \frac{2}{n}\sum_{i=1}^{n} P_i \sin\frac{2pki}{n} \quad (i = 1, 2, \ldots, k) \tag{6}$$

When the periodic component is extracted, it should be eliminated. The method is the same with both trend and seasonal components.

Random component is the last one to be extracted. It can be influenced by many uncertain factors, such as noise. It can be extracted by the autoregression method.

$$\hat{R}_t = \Phi_0 + \Phi_1 r_{t-1} + \Phi_2 r_{t-2} + \cdots + \Phi_p r_{t-p} \tag{7}$$

where p is the model order which is determined by the Akaike information criterion (AIC) and Φ_i is the autoregressive coefficient. When the value of AIC(p) is minimum, the p value is fixed.

$$\mathrm{AIC}(p) = n \ln \hat{\sigma}_p^2 + 2p \tag{8}$$

where n is the amount of datum and $\hat{\sigma}_p^2$ is the variance of the residuals of AR(p).

In this study, the positions of wells were selected according to the isoclines of groundwater level charts based

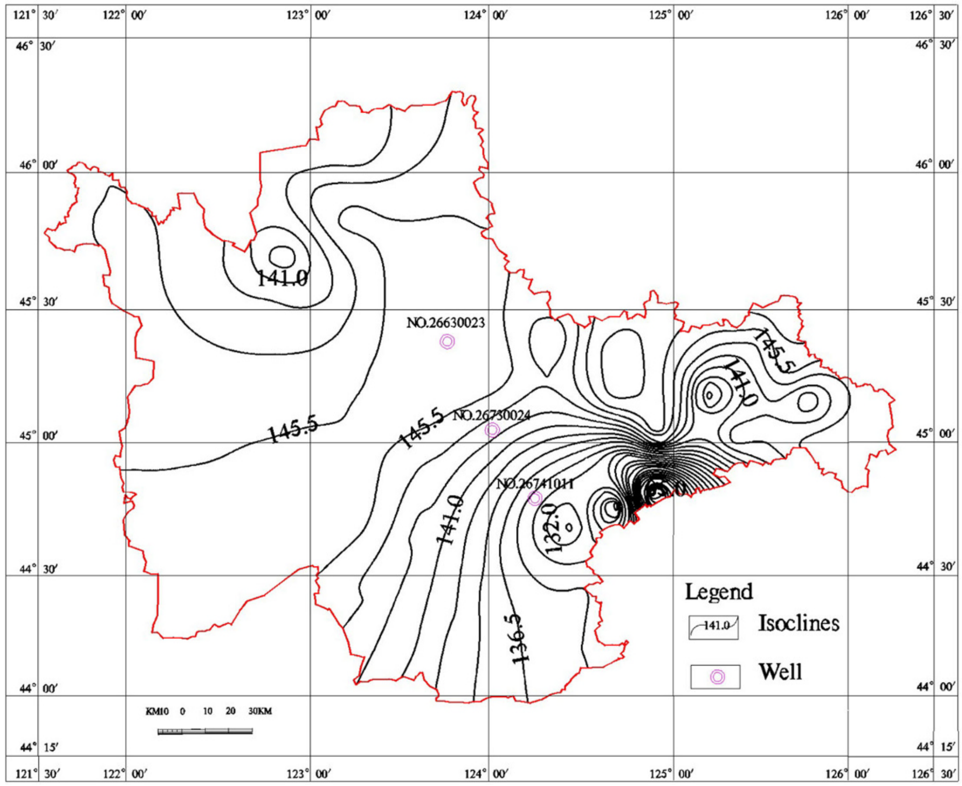


Fig. 1 The isoclines of groundwater level chart in the year 2009 in the western Jilin Province

on the groundwater level of 50 wells in the year 2009 in the western Jilin Province (Fig. 1). Then, No. 26741011 well in Changling (upstream), No. 26730024 in Qian'an (midstream) and No. 26630023 in Da'an (downstream) were chosen as the representative wells in the western Jilin Province for the analysis. The reason for choosing these three wells is that they are located in the direction of groundwater flow based on the isoclines of groundwater levels. The groundwater levels observed monthly over a period 26 years (1986–2011) were used. The time series of the first 22 years (1986–2007) was used to create the model, and it was then tested for accuracy using the most recent 4-year data (2008–2011). Finally, the model was then used to forecast the variation of groundwater levels in the following 3 years.

Results and discussion

Establishing model

At first, using the moving average method twice and then adopting stepwise regression method, the trend component is found (Fig. 2). The equations for trend component are as follows:

$$\hat{X}_t = 0.8976 + 10.5371t^{-1} + 0.2868t^{1/2} - 23.2042e^{-t} \quad (9)$$

$$\hat{X}_t = -4.0635 + 2.9321t^{-1} + 4.4312t^{1/10} \quad (10)$$

$$\hat{X}_t = 1.1819 + 7.8731t^{-1} + 0.2634t^{1/2} - 17.2344e^{-t} \quad (11)$$

The results show that the trend of groundwater depth shows an increase in all regions year by year. Because the exploitation by humans in Changling is the heaviest, the groundwater depth there increases the fastest. As the well located in Da'an is in an irrigated area, the groundwater depth increases the slowest under the combination of human exploitation and irrigation return flow.

After excluding the trend component, we calculate the average of $H(t) - X(t)$ (additive model) or $H(t)/X(t)$ (multiplicative model) of the same month data in different years. The results are shown in Table 1.

The results show that mostly from January to June, the seasonal components of the additive model are negative and from July to December, positive. From January to June the seasonal components of the multiplicative model are bigger than 1 and from July to December less than 1. The reason is that the rainy season begins in June and the rise in groundwater level is delayed and often begins in July. Among the three seasonal components of the different places, it can be found that seasonal component in Changling (upstream) varies the most. This phenomenon may be attributed to the natural condition: that is, the average annual precipitation in Changling is the heaviest and the average annual evaporation is the least.

Using harmonic wave analysis to $H(t) - X(t) - S(t)$ or $H(t)/X(t)/S(t)$ to extract the periodic component, we draw

Fig. 2 The trend fitting charts (**a** Changling, **b** Qian'an and **c** Da'an)

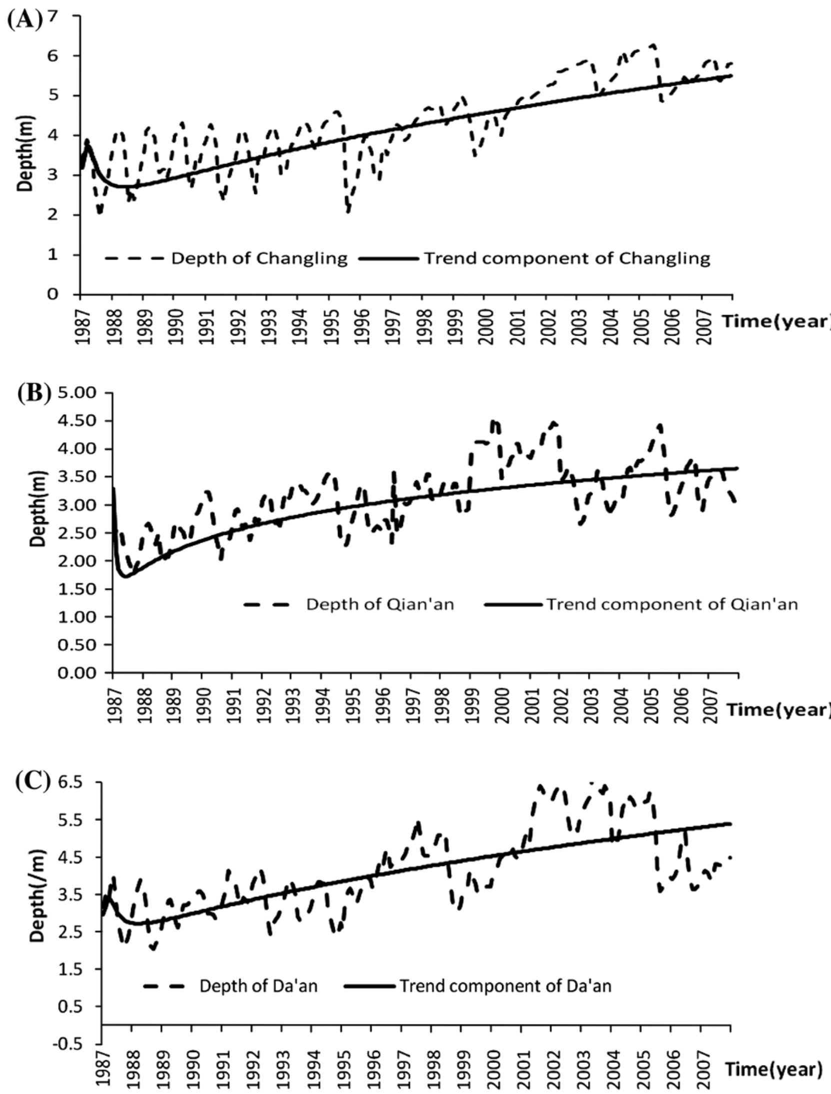


Table 1 Seasonal value of the depth to the water table in the western Jilin Province

Month	Additive model $\hat{S}_t$ (m)			Multiplicative model $\hat{S}_t$ (m)		
	Changling	Qian'an	Da'an	Changling	Qian'an	Da'an
1	0.28	0.02	−0.05	1.08	1.01	0.99
2	0.45	0.20	0.14	1.13	1.08	1.04
3	0.50	0.27	0.31	1.14	1.10	1.08
4	0.47	0.25	0.39	1.13	1.09	1.11
5	0.36	0.14	0.44	1.10	1.04	1.11
6	0.01	0.14	0.31	0.99	1.04	1.07
7	−0.27	0.01	0.02	0.91	1.00	0.99
8	−0.47	−0.20	−0.21	0.86	0.92	0.94
9	−0.34	−0.23	−0.26	0.90	0.91	0.92
10	−0.23	−0.14	−0.26	0.93	0.94	0.92
11	−0.12	−0.12	−0.26	0.96	0.95	0.93
12	0.04	−0.02	−0.14	1.01	0.99	0.96

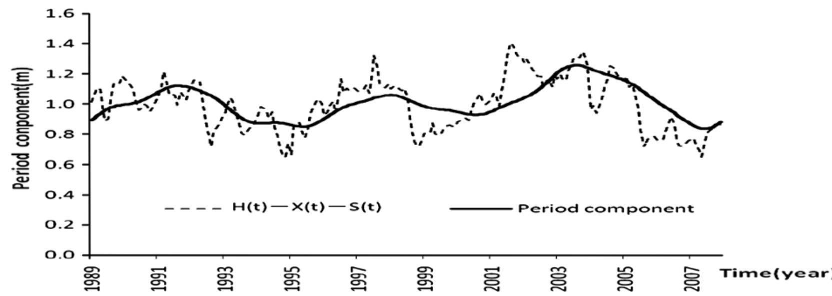


Fig. 3 The period component fitting chart in Changling

the conclusion that the groundwater levels show 6–9 years periodicity. This periodicity is believed to be driven by the cycle of solar activity and the Earth's rotation and revolution (Zheng 1989). Sunspot activity can influence the alternation of the dry and rainy seasons. Thus, the periodicity reflects the natural factor of climate. For example, take the multiplicative model of Changling. Figure 3 shows nearly three waves during 18 years with a time of period about 6 years. The equation of the period component of the additive model in Changling is as follows:

$$\begin{aligned}\hat{P}_t = & -0.0227 - 0.0395\cos\left(\frac{2\pi}{228}\times 9t\right) + 0.0506\sin\left(\frac{2\pi}{228}\times 9t\right)\\ & + 0.1531\cos\left(\frac{2\pi}{228}\times 6t\right) + 0.1172\sin\left(\frac{2\pi}{252}\times 6t\right)\\ & + 0.1818\cos\left(\frac{2\pi}{228}\times t\right) - 0.1058\sin\left(\frac{2\pi}{228}\times t\right)\\ & + 0.4123\cos\left(\frac{2\pi}{228}\times 3t\right) - 0.051\sin\left(\frac{2\pi}{228}\times 3t\right)\\ & + 0.0068\cos\times\left(\frac{2\pi}{228}\times 7t\right) + 0.0707\sin\left(\frac{2\pi}{228}\times 7t\right)\\ & + 0.326\cos\left(\frac{2\pi}{228}\times 2t\right) - 0.0347\sin\left(\frac{2\pi}{228}\times 2t\right)\end{aligned} \quad (12)$$

After excluding the trend, and seasonal and periodic components, the random component is analyzed by the autoregression method (Fig. 4). The equation of multiplicative model in Changling is as follows:

$$\begin{aligned}\hat{R}_t &= \Phi_1 r_{t-1} + \Phi_2 r_{t-2} + \Phi_6 r_{t-6} + \Phi_8 r_{t-8} + \Phi_9 r_{t-9}\\ &= 1.1719 r_{t-1} - 0.3735 r_{t-2} + 0.1079 r_{t-6} + 0.0436 r_{t-8}\\ &\quad + 0.0447 r_{t-9}.\end{aligned} \quad (13)$$

Model test

After all components are examined and analyzed, it is time to combine all the models together. Either adding or multiplying those four will generate the forecast model. The results of the test can be seen in Fig. 5.

$$\hat{H}_t = \hat{X}_t + \hat{S}_t + \hat{P}_t + \hat{R}_t \quad (14)$$

$$\hat{H}_t = \hat{X}_t \times \hat{S}_t \times \hat{P}_t \times \hat{R}_t \quad (15)$$

Before forecasting the groundwater level, whether these models are accurate is tested. The after-test residue method tests the accuracy of the model, that is to say, by calculating the two parameters c and P (Chen et al. 1994; Lu et al. 2012).

$$c = s_2/s_1 \quad (16)$$

$$p = \{|e(k) - e| < 0.6745 s_1\} \quad (17)$$

where s_1 refers to the root mean-square error of the sample data, s_2 refers to the root mean-square error of residual data, $e(k)$ is the residual of data and e is the average of residuals. The standard of c and P value is shown in Table 2. If $c < 0.35$ and $P > 0.95$, the model can be used for prediction, otherwise the model should be examined and adjusted until the parameters c and P fit the standard.

Using Excel, we obtained the c and P values of both additive and multiplicative models (Table 3). All the c values are <0.35 and the P value is >95 %. Therefore, the models are good enough to forecast the groundwater levels.

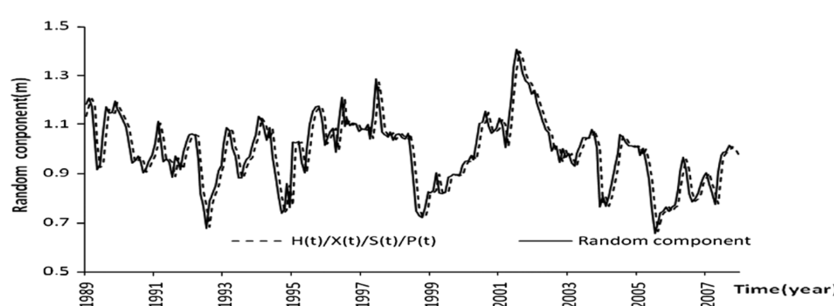


Fig. 4 The random component fitting chart in Changling

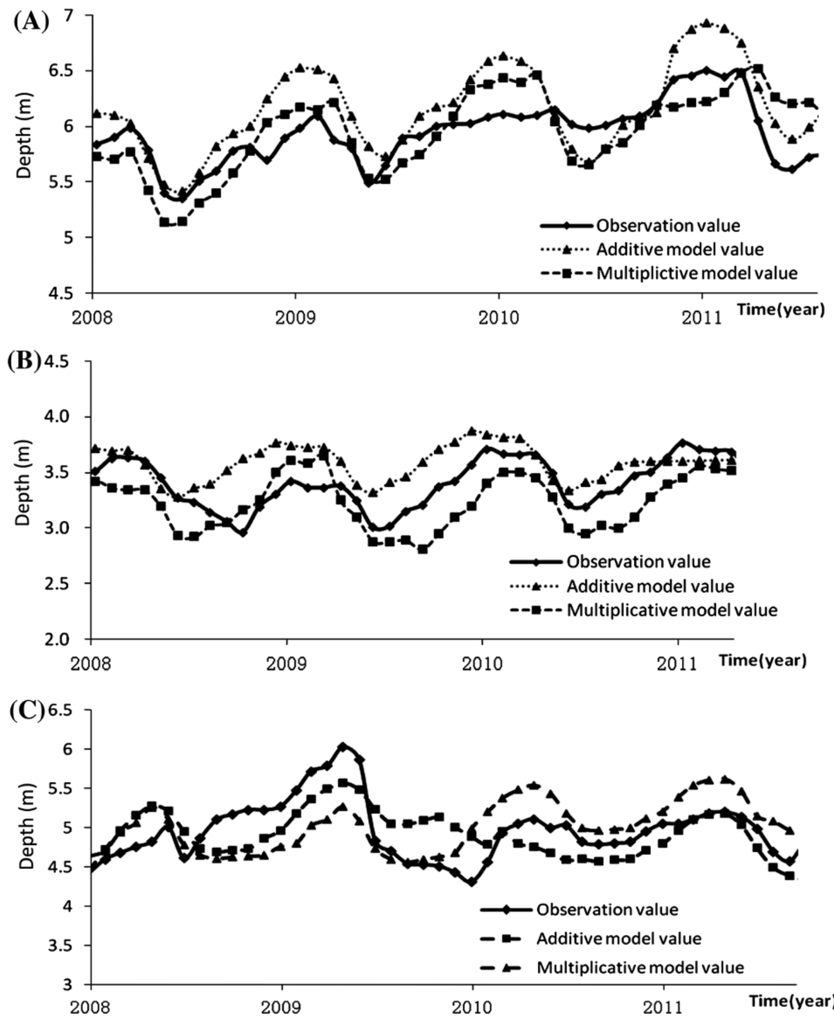


Fig. 5 Test results (**a** Changling, **b** Qian'an and **c** Da'an)

Table 2 Standard of the test

Grade	*c* value	*P* value (%)
Good	<0.35	>95
Qualified	0.35–0.50	80–95
Just at the mark	0.50–0.65	70–80
Below the mark	>0.65	<70

Table 3 *c* and *P* value results of the two models

Place	*c* in add model	*P* in add model (%)	*c* in multiplicative model	*P* in multiplicative model (%)
Changling	0.27	100	0.18	100
Qian'an	0.25	100	0.28	100
Da'an	0.14	100	0.15	100

The contrast between the additive and multiplicative models

As shown in Table 2, *c* value of the multiplicative model (0.18) is smaller than that of the additive model (0.27) in Changling; however, in Qian'an and Da'an *c* value of the additive model (0.25, 0.14) is smaller than that of the multiplicative model (0.28, 0.15). Generally speaking, the smaller *c* is, the better it fits. Thus, the multiplicative model fits Changling better and the additive model fits Qian'an and Da'an better. The multiplicative model is generally suitable for the sequence where seasonal and period components are not obvious (Zhang and Yang 2005). The additive model fits the sequence where seasonal and period components are obvious. On the contrary, the multiplicative model is generally suitable for the sequence where seasonal and period components are not obvious (Zhang and Yang 2005). The soil types in Changling, Qian'an and Da'an are chernozem, quaternary unconsolidated rock and alluvial sand, respectively. Thus, the permeability of Changling is poor and it is good in Qian'an and Da'an. So the groundwater levels in Changling fluctuate slightly and its seasonal and period components are not obvious. As a result, the multiplicative model fits the hydrogeological conditions in Changling better. In the same way of analysis, the additive model fits the hydrogeological conditions in Qian'an and Da'an.

Model prediction

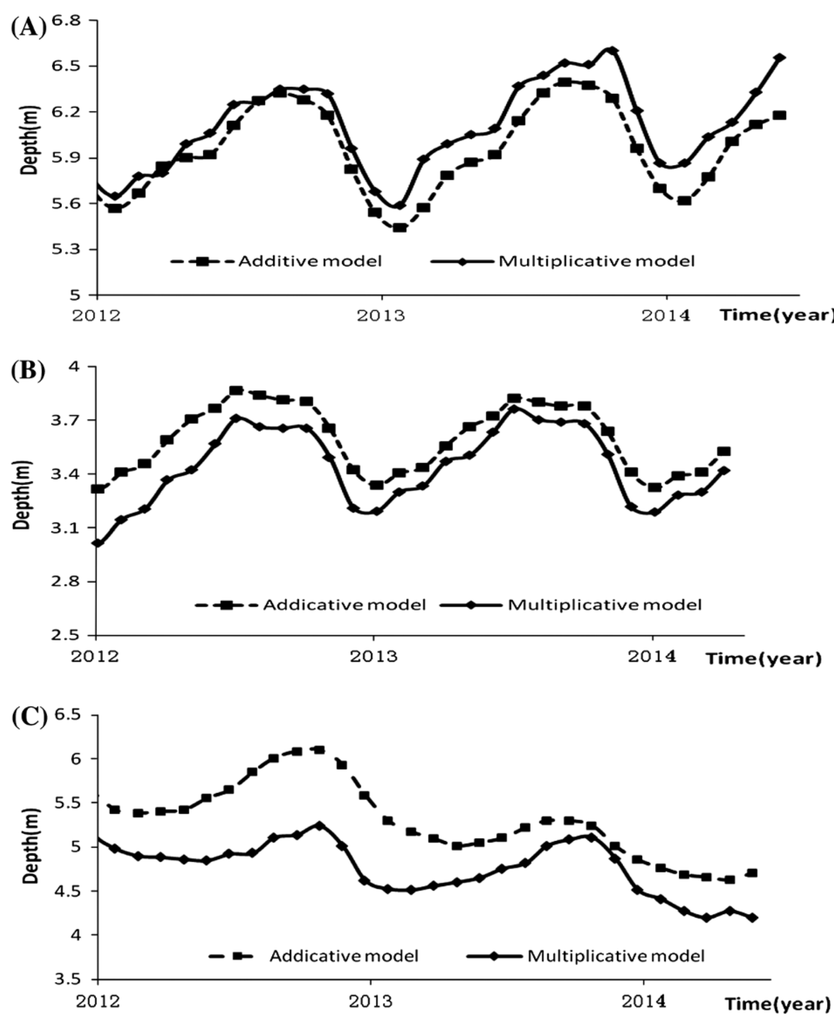
Next, we used the models to predict the groundwater level in the next 3 years (2012–2014). The results are shown in Fig. 6.

The space comparison among the groundwater levels located in the upper, middle and downstream areas

The relationship of the groundwater levels located in the upper, middle and downstream areas is presented in Fig. 7.

According to Fig. 7, the correlation of the groundwater level time series of the three wells is very good for the years before 1995. They show consistent variation. Almost on the same month the highest and lowest levels are reached. On the contrary, after 1995 the correlation deteriorated and the water level in each well behaved independently. In upstream and midstream, the trend of groundwater level showed an increase. However, in the downstream, it decreases. Furthermore, the increasing trend in the upstream and midstream was different. The highly correlated groundwater level fluctuations over the years before 1995 may be attributed to the influence of natural factors. The low correlation after 1995 may be due to anthropogenic activities. In the year 1995, the provincial government took measures for western agricultural development and constructed a large number of irrigation wells (Liu et al. 2000). The extraction of groundwater resources was 400 million m^3 per year in 1990. However, it was 791 million m^3 per year in 1995, nearly two times of that in 1990 (Fig. 8a).

Fig. 6 The prediction results of two models



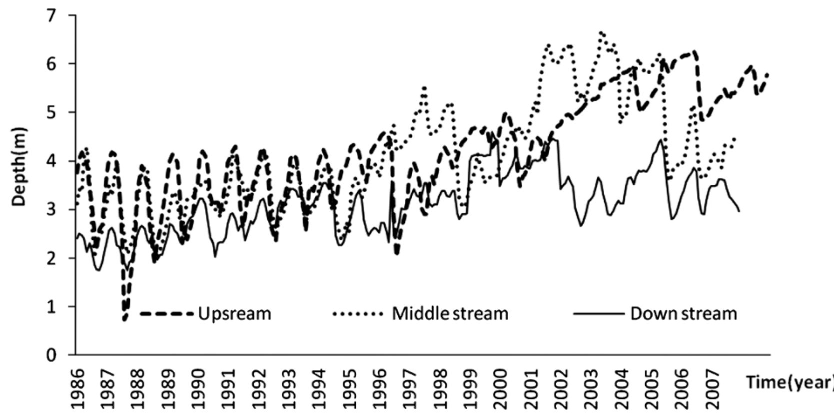


Fig. 7 The space comparison chart of water depth in the upper, middle and downstream places

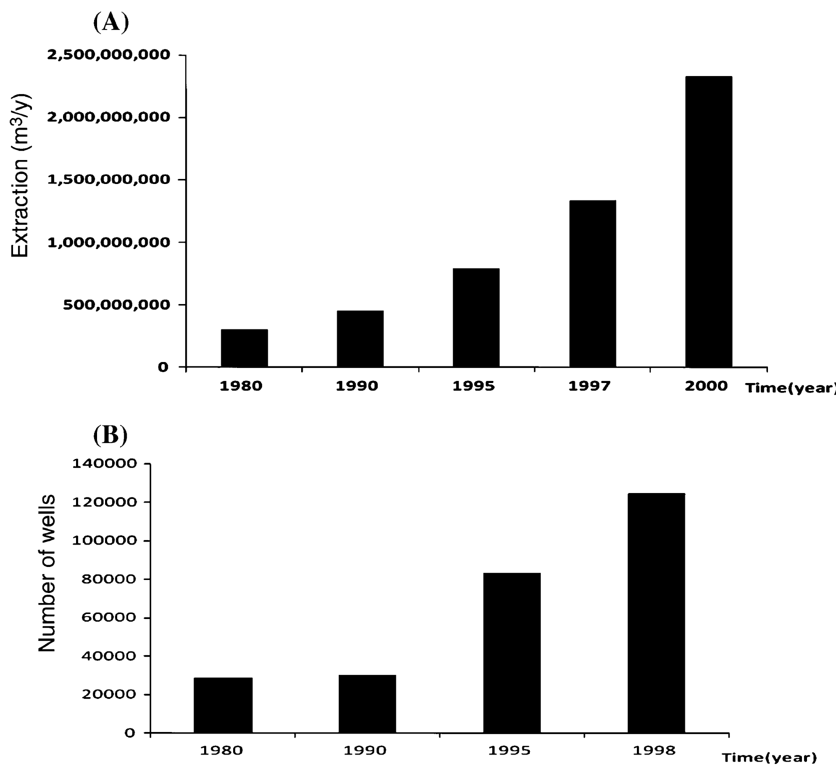


Fig. 8 The condition of extraction

In addition, the number of irrigation wells in 1995 was nearly three times that in 1990 (Fig. 8b). Furthermore, the nonhomogenous distribution and extraction rate of irrigation well in these areas also contribute to the different fluctuation trend for groundwater level after 1995. Also, the recharge to the surface water is also spatially different. In general, rivers slightly gain upstream, and then start losing and finally gain again as they exit the basin (Baalousha 2012).Thus, human activities are the likely causes for the fluctuation of the groundwater levels in the western Jilin Province. With the differences in the magnitudes of groundwater exploitation, the groundwater depths increase differently. Therefore, the groundwater level data for the three well do not correlate with each other and vary independently. In addition, as the groundwater levels decline, the risk of exploiting groundwater is growing (Han et al. 2011).

The comparison with another time series analysis model called ARIMA

There are many models in time series analysis, such as the ARMA, ARIMA and GARCH. Here, we compare the ARIMA model with the decomposition method to observe the prediction results. This model possesses high precision and simple operation. Based on the software Eviews6.0 and groundwater levels of three wells in 1986–2011, the ARIMA(4,1,1), ARIMA(3,1,1) and ARIMA(2,1,1) were established to perform the prediction analysis in the upper, middle and downstream areas, respectively. The c value of

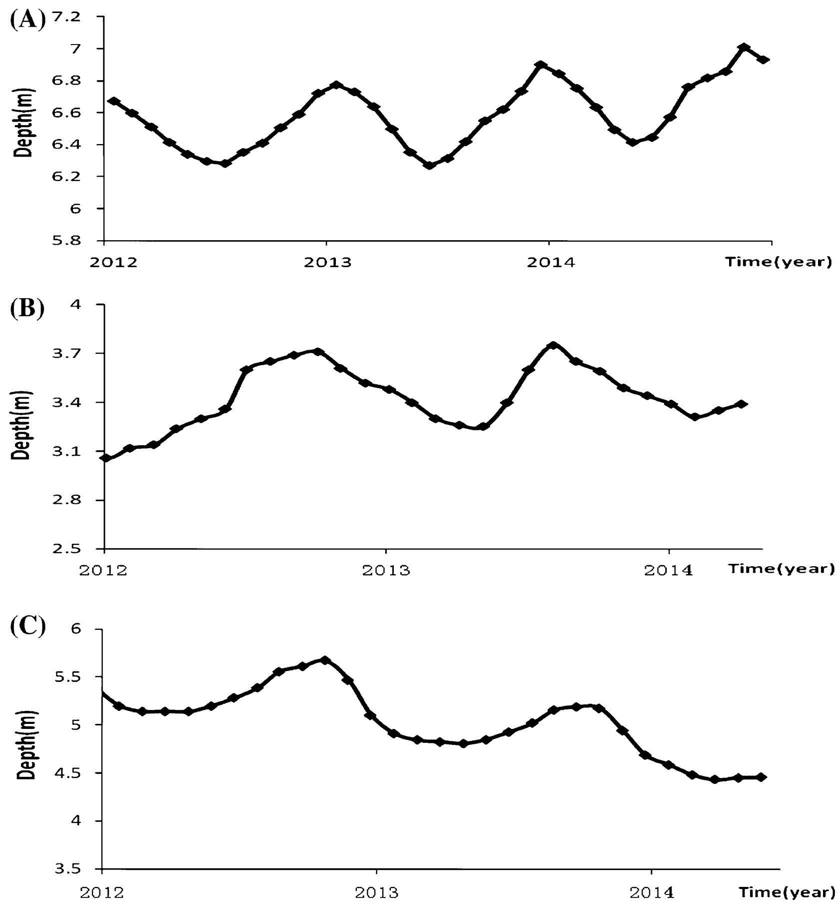


Fig. 9 The prediction results of the ARIMA model (**a** Changling, **b** Qian'an and **c** Da'an)

the ARIMA model during the process of model test is 0.34, 0.29 and 0.16, respectively. That is to say, the ARIMA model is good and it is ready to deliver forecast behavior, but not as good as the decomposition method. The forecast results can be seen in Fig. 9.

Conclusions

The decomposition method shows that the groundwater levels decrease rapidly with the excessive exploitation by humans. Moreover, they are influenced by rainfall obviously, which increased from July to November and declined from December to June of the next year. Furthermore, they are associated with the cycle of solar activity and the Earth's rotation and revolution, such that they exhibit 6–9 years' periodicity.

The integrated use of the additive and multiplicative models can be adapted to different hydrogeological conditions. By contrast, in areas with poor soil permeability, the multiplicative model fits better than the additive model. In areas with good soil permeability, the additive model fits better than the multiplicative model.

Consistent variations of groundwater levels located in the upper, middle and downstream areas before 1995 may manifest the effects of natural factors. However, after 1995 the consistent variation among them disappeared. This indicates that the impact of human factor on groundwater level has become significant. This study also predicts the groundwater level behaviors in the next 3 years. This information can be used for groundwater management purposes.

Both ARIMA model and decomposition method could meet the forecast accuracy, but ARIMA could not show the characteristics of groundwater level fluctuation (such as periodicity); so, the decomposition method is recommended for the analysis of the dynamic characteristics of groundwater level.

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